A00-37262

AIAA-2000-4305

NEURAL-NETWORK-BASED MODELING OF ROTORCRAFT VIBRATION FOR REAL-TIME APPLICATIONS

Sesi Kottapalli
Aeromechanics Branch
Army/NASA Rotorcraft Division
NASA Ames Research Center
Moffett Field, California

Summary

The overall objective of this ongoing effort is to provide the capability to model and simulate rotorcraft aeromechanics behaviors in real-time. This would be accomplished by the addition of an aeromechanics element to an existing high-fidelity, real-time helicopter flight simulation. As a first step, the peak vertical vibration at the pilot floor location was considered in this neural-network-based study. The flight conditions considered were level flights, rolls, pushovers, pull-ups, autorotations, and landing flares. The NASA/Army UH-60A Airloads Program flight test database was the source of raw data. The present neural network training databases were created in a physically consistent manner. Two modeling approaches, with different physical assumptions, were considered. The first approach involved a "maneuver load factor" that was derived using the roll-angle and the pitch-rate. The second approach involved the three pilot control stick positions. The resulting, trained back-propagation neural networks were small, implying rapid execution. The present neural-network-based approach involving the peak pilot vibration was utilized in a quasi-static manner to simulate an extreme, time-varying pull-up maneuver. For the above pull-up maneuver, the maneuver load factor approach was better for real-time simulation, i.e., produced greater fidelity, as compared to the control stick positions approach. Thus, neural networks show promise for use in high-fidelity, real-time modeling of rotorcraft vibration.

Introduction

In order to expedite pilot training, it is important for any flight simulator to achieve a high degree of functional fidelity, i.e., the adequacy of piloted

simulation. An example taken from currently used simulators is the Vertical Motion Simulator (VMS) at NASA Ames. The VMS is a high-fidelity, piloted, six degree-of-freedom, real-time flight simulator.[1-3] It allows for the greatest motion range of any flight simulator in the world. The Ames VMS can simulate a variety of aircraft including rotorcraft (not including some aeromechanics behaviors), the Space Shuttle Orbiter, and others. A vibration model of the UH-60A has been used for many years in the Ames VMS to simulate pilot seat-shake.[4] The associated flight test data based, seat-shaker algorithm does not involve neural networks.

Currently, rotorcraft aeromechanics behaviors are not adequately modeled in simulators. These aeromechanics behaviors include pilot vibration and cabin noise. Thus, future research could be directed towards inclusion of both cockpit vibration and noise. In this first-time study, helicopter vibration was modeled using neural networks. The non-inclusion of vibration in the simulations of severe and/or complex maneuvers could have an adverse effect on pilot performance because such maneuvers entail high vibration levels. It is thus important to extend the existing real-time simulation capabilities by the addition of rotorcraft aeromechanics behaviors, especially vibration.

Existing neural-network-based work covered real-time rotor system flight test load monitoring systems for the Navy SH-60 helicopter.[5-7] On-line evaluation of flight vibratory loads was studied.[5] The present study, however, covers neural-network-based, high-fidelity real-time ground based simulator modeling of pilot floor vertical vibration for the Army UH-60A helicopter. Neural network studies on rotorcraft performance, acoustics, and dynamics were initiated in the Army/NASA Rotorcraft Division at NASA Ames Research Center.[8-13]

The present neural-network-based results provide the capability to model rotorcraft aeromechanics behaviors in real-time. Specifically, the capabilities of the existing high-fidelity, real-time flight simulation would

		Form Approved OMB No. 0704-0188

Report Documentation Page

Form Approved
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE **2000**	2. REPORT TYPE	3. DATES COVERED **00-00-2000 to 00-00-2000**

4. TITLE AND SUBTITLE **Neural-Network-Based Modeling of Rotorcraft Vibration for Real-Time Applications**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **US Army Aviation and Missile Command,Army/NASA Rotorcraft Division,Aeromechanics Branch,Moffett Field,CA,94035**	8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT **Same as Report (SAR)**	18. NUMBER OF PAGES **16**	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**			

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

be extended. This would be accomplished by the addition of an aeromechanics element.

For purposes of modeling the UH-60A vibration, two analytical approaches, involving different physical assumptions, were considered. This resulted in three neural-network-training databases. The first database involved a maneuver load factor that was derived using the helicopter roll-angle and its pitch-rate. The second and third databases involved the three pilot control stick positions. In the first and second databases, the helicopter gross weight was included as one of the neural network inputs. The third database was the same as the second database, except that the gross weight was not included.

In general, to obtain a time varying, step-by-step simulation of the pilot vibration during a maneuver, a neural network based time-series method can be used. However, such methods are complex. In the present, first-time modeling study using neural networks, a static-mapping approach involving the peak vibration level was followed. This implied that each flight condition was characterized by its peak vibration. The possibility of utilizing the present, peak-vibration-based static mapping in a quasi-static manner to simulate time varying maneuvers was also investigated. That is, the fidelity of a quasi-static, real-time simulation was studied. A quasi-static approach will not capture all dynamic effects, and may miss the prediction of relevant maximums and their associated phases. Also, a time-series analysis using neural networks will capture the maximums and phases more accurately, compared to a quasi-static approach. It should be noted that the present quasi-static approach represents one way of simulating maneuvers. The present work provides the capability of real-time simulation of pilot vibration for the entire UH-60A flight envelope.

The present use of neural networks was justified because of the following two reasons. First, trained neural networks can be rapidly executed, an advantage in real-time applications. Second, neural networks can perform multi-dimensional, nonlinear curve fitting, an advantage in high-fidelity applications. The present work is considered to be a generic methodology and is not specific to the presently considered rotorcraft configuration.

Objectives

The present neural-network-based modeling study involving the peak, N/rev pilot floor vertical vibration had the following three objectives:

1. Create two compact neural network training databases, one involving the helicopter body motions and the other involving the pilot controls.

2. Study the fidelity considerations using a) neural networks and the above maneuver load factor, and separately, b) neural networks and the three control stick positions.

3. Quantify the advantages and disadvantages of using the three training databases.

Vibration Neural Network Databases

The source of the presently used raw data was the NASA/Army UH-60A Airloads Program flight test database.[14, 15] The present study included the following flight conditions: level flights, rolls, pushovers, pull-ups, autorotations, and landing flares. The creation of the present three compact neural-network-training databases involved a substantial amount of manual effort and time.

Description of Present Databases

A single neural network output, common to all three training databases, was considered. The peak, N/rev pilot vertical floor vibration, peak PVV, was the neural network output. The overall approach used to obtain the peak PVV is discussed later, under "Database Construction Example I: Pull-up" and also under "Database Construction Example II: Autorotation."

Database 1 This neural network training database involved six inputs that are given as follows:

  i) Advance ratio.
  ii) Gross weight, lbs.
  iii) Main rotor rotational speed, RPM.
  iv) Density ratio.
  v) Maneuver load factor, MLF, discussed below.
  vi) Ascent/descent rate, fpm.

The MLF, a non-dimensional parameter, was used to characterize aircraft maneuvers involving simultaneous non-zero roll-angle and pitch-rate. In the present study, the MLF was defined by the following equation:

Maneuver load factor, MLF =
$$[1 / \cos (\text{roll-angle})] * [1 + (\text{pitch-rate} * \text{airspeed} / g)]$$

(1)

where "g" is the acceleration due to gravity. The flight-path axis system[16] was used. The purpose of the MLF was to compactly represent complex maneuvers using a single, physics-based parameter. Depending on the reference axes system used, other parameters can be derived, and this would result in slightly different formulations.

Database 1 involved two aircraft parameters, the angle-of-bank and the pitch-rate. The other two databases do not involve these two parameters, but involve the three pilot control stick positions.

Database 2 This neural network training database involved eight inputs that are given as follows:

    i)   Advance ratio.
    ii)   Gross weight, lbs.
    iii) Main rotor rotational speed, RPM.
    iv)   Density ratio.
    v)   Collective stick position, %
    vi)   Lateral stick position, %
    vii) Longitudinal stick position, %
    viii) Ascent/descent rate, fpm.

Database 3 This neural network training database was obtained after removing the gross weight from the database 2 input list. Thus, database 3 involved seven . inputs that are given as follows:

    i)   Advance ratio.
    ii)   Main rotor rotational speed, RPM.
    iii) Density ratio.
    iv)   Collective stick position, %
    v)   Lateral stick position, %
    vi)   Longitudinal stick position, %
    vii) Ascent/descent rate, fpm.

The flight test data were represented in the neural network training databases in a physically consistent manner. Physically consistent refers to the manual extraction of the correct values of relevant parameters, e.g., the correct pitch-rate associated with a pull-up maneuver. Presently, the correct pitch-rate was taken as that corresponding to the peak PVV. Let the peak PVV occur at a time $t = \tau$. The correct pitch-rate was defined as that also occurring at time $t = \tau$. In general, the peak-PVV-time, τ was different for different maneuvers, and had to be individually determined.

Database Construction Example I: Pull-up

A pull-up maneuver at approximately 120 knots was considered in this example. In the UH-60A flight test database,[14, 15] counter 11022 represented a pull-up maneuver. This maneuver represents an extreme maneuver. The pitch-rate associated with this particular maneuver is extreme, one that was employed intentionally for test purposes, or one that might be employed by the pilot to accomplish a sudden evasive action. For this flight condition, the gross weight was 16055 lbs, the rotor RPM was 255, and the advance ratio was 0.27. The time history record duration was 37 seconds (156 rotor revolutions).

The present study attempts to reconcile the aeromechanics and flight mechanics aspects. In this initial study, unfiltered time history records are shown. For flight mechanics considerations, helicopter body motions up to 10 read/sec are important.

Figure 1 shows the time history of the instantaneous pilot floor vertical acceleration for the above pull-up. To obtain a time varying, step-by-step simulation of the acceleration time history shown in Fig. 1, a neural network based time-series method can be used. In the present modeling study using neural networks, a static-mapping approach involving the peak vibration level was followed. Figure 2 shows the pitch-rate time history for the same counter, 11022. Figure 3 shows the corresponding time-histories of the three pilot control stick positions, the collective, longitudinal and lateral cyclics. It should be noted that the filtered pilot control stick position variations would not contain the high frequency components present in the unfiltered data shown in Fig. 3.

Pilot Floor Vertical Vibration Figure 4 shows the 4P component of the pilot floor vertical acceleration. This 4P component, Fig. 4, was obtained by breaking up the time history record, Fig. 1, into intervals of 8 revolutions each. In this study, the 4P component of the pilot floor vertical acceleration was referred to as the pilot vertical vibration, PVV. Presently, the PVV was obtained by performing a harmonic analysis[15] of the acceleration time-history in which the individual time-segments (time windows) were eight rotor revolutions long. Some dynamic effects may not be accurately modeled if the sample length used in the harmonic analysis is too large. At the same time, a too-small sample length will introduce spurious dynamic information. Future, detailed studies could focus on determining an appropriate sample length for the present application. Such a time window study would need to consider all maneuvers, make detailed comparisons of the resulting PVV's, and determine the appropriate sample length. Figure 4 shows that the peak PVV for the above pull-up was 0.22 g's.

Pitch-Rate The correct pitch-rate, used in calculating the maneuver load factor in database 1, for the above pull-up maneuver, counter 11022, was that corresponding to the peak PVV, Fig. 4. The correct pitch-rate, Fig. 2, was determined to be 9.6 deg/sec. The subject pull-up involved a negligible roll-angle, resulting in a maneuver load factor, MLF = 2.0.

Pilot Control Stick Positions The three control stick positions (databases 2 and 3) for the above pull-up maneuver, counter 11022, were manually obtained as those corresponding to the peak PVV, Fig. 4. The positions of the collective, lateral and longitudinal

cyclic controls at the time when the PVV was maximum were 76%, 60%, and 57%, respectively.

<u>Database Construction Example II: Autorotation</u>

An autorotation at approximately 60 knots was considered in this example. In the UH-60A flight test database,[14,15] the two counters 11539 and 11540 represented two segments of the selected single autorotation condition. For this flight condition, the approximate gross weight was 15910 lbs, the rotor RPM was 256, and the advance ratio was 0.17. The time history record duration for each segment was 27 seconds (115 rotor revolutions). The main rotor shaft power and the pilot collective stick position were the two helicopter performance parameters required to establish autorotation conditions.

Figure 5 shows the time histories of the pilot floor vertical acceleration and the main rotor shaft power for segment 1. The reduction in shaft power, starting just prior to 10 seconds, marks the beginning of the autorotation phase. Figure 6 shows the time history for the collective stick position for segment 1.

Figure 7 shows the time histories of the pilot floor vertical acceleration and the main rotor shaft power for segment 2. The resumption of power to the shaft occurs after 10 seconds and marks the end of the autorotation phase. Figure 8 shows the time history for the collective stick position for segment 2. Figures 7 and 8 show that the post-autorotation phase occurs in segment 2 and starts after 10 seconds.

<u>Pilot Floor Vertical Vibration</u> Figure 9 shows the 4P component of the pilot floor vertical acceleration for segments 1 and 2. The 4P component was obtained from the acceleration time histories shown in Figs. 5 and 7. Figure 9 shows that the peak 4P component of the pilot floor vertical acceleration for the complete autorotation condition occurred during its post-autorotation phase, segment 2 (for this particular maneuver). Figure 9 shows that the peak PVV was 0.26 g's.

For the above, complete autorotation condition, the neural network inputs needed in constructing the three databases were those corresponding to the peak PVV, Fig. 9, and involved data from segment 2, counter 11540.

Neural Network Approach

To accurately capture the required functional dependencies, the neural network inputs must be carefully selected and account for all important physical traits that are specific to the application. The important attributes of a neural network are its type (radial-basis

function network or back-propagation network, etc.) and its complexity (i.e., the number of processing elements (PEs) and the number of hidden layers). The present overall neural network modeling approach[8-13] consists of first determining the best type of neural network to be used and then simplifying the network as much as is practical.

Determining the best type of neural network usually involves selecting either a radial-basis function (RBF) or a back-propagation network. The RBF network (Moody-Darken version) can be used in most situations in which one would consider using a back-propagation network.[17] In the present study, the back-propagation type of network was used.

Simplifying the network involves reducing the number of PEs and in a few cases, the number of hidden layers. The number of PEs required depends on the specific application. The determination of the appropriate number of PEs is done by starting with a minimum number of PEs. Additional PEs are added to improve neural network performance by reducing the RMS error between the test data and the neural network predictions. Typically, five PEs are added at each step in this process. Adding two or three PEs at a time fine-tunes the neural network.

If the correlation plot, comparing measured and predicted values, shows only small deviations from the 45-deg reference line, the neural network has produced an acceptable representation of the subject test data. If the plot shows points well off of the 45-deg line, the presence of "bad" test data is assumed. A detailed examination of the subject test database is then required to identify the source(s) of the errors associated with these test data.

The notation used in this paper to characterize a neural network is described as follows. A neural network architecture such as "4-25-5-1" refers to a neural network with four inputs, twenty five processing elements (PEs) in the first hidden layer, five PEs in the second hidden layer, and one output.

The application of neural networks to full-scale helicopter flight test vibration data was conducted using the neural networks package NeuralWorks Pro II/PLUS (version 5.2) by NeuralWare.[17] The present neural network RMS error was dimensionless and based on the squares of the errors for each processing element (PE) in the output layer. Generally, the RMS error was characterized by a monotonic decrease with the number of training iterations.[12] Also, any large differences in the magnitudes of the neural network variables were mitigated by appropriate scaling. In the present application, the cost function used in minimizing the

RMS error had equally weighted individual contributions.

The number of training data points was over 200. Approximately 25% of this training database involved maneuver-related points, in the maneuver categories referred to earlier. Here, maneuver-related refers to a flight condition for which the maneuver load factor, MLF $\neq$ 1. In the present study, the single neural network output was the UH-60A peak, pilot floor vertical vibration (peak PVV). Neural-network-based modeling results for the peak PVV are given in this paper in the form of correlation plots. The neural-network-predicted peak PVV is plotted versus the corresponding flight test peak PVV.

Results

Figure 10 shows the correlation obtained using the maneuver load factor, MLF, approach (database 1). Figure 10 shows the correlation plot from a MISO 6-10-5-1 back-propagation neural network. The back-propagation network was trained for 4 million iterations with a final RMS error of 0.07. Figure 10 shows that the corresponding error-band was +/- 0.05 g's. The maneuver load factor approach, database 1, gave acceptable results.

Figure 11 shows the correlation obtained using the control stick approach (database 2). Figure 11 shows the correlation plot from a MISO 8-10-5-1 back-propagation neural network. The back-propagation network was trained for 550,000 iterations with a final RMS error of 0.07. Figure 11 shows that the corresponding error-band was +/- 0.05 g's. The pilot control stick approach, database 2, gave acceptable results.

Figure 12 shows the correlation obtained using the control stick approach (database 3, gross weight not included). Figure 12 shows the correlation plot from a MISO 7-10-5-1 back-propagation neural network. The back-propagation network was trained for 1.75 million iterations with a final RMS error of 0.07. Figure 12 shows that the corresponding error-band was +/- 0.05 g's. The pilot control stick approach, database 3 with the helicopter gross weight not included, gave acceptable results.

To summarize the above results, Figs 10-12, both the maneuver load factor approach and the pilot control stick approach were shown to be reasonable approaches for statically-mapped vibration. In this context, Figs. 10-12 showed that the same level of modeling accuracy could be obtained from either approach. Also, the present, trained back-propagation neural networks were small, implying rapid execution.

A comparison of Figs. 10-12 brought up an interesting data-quality consideration. It should be noted in Figs 10-11, that a few experimental data points close to 0.10 g's were modeled to produce neural-network-based results that were close to the +0.05 g's error line. In Fig. 12, the neural-network-based result for one of the "0.10 g's" experimental point clearly fell outside of the +0.05 g's error line. An examination of database 3 showed that this point was associated with a roll-maneuver. This implied that it was necessary to include the gross weight as an input for maneuvers for the cases presently considered with the given approach.

Quasi-Static Real-Time Simulation

Selected results taken from Figs. 10-12 are shown in Table 1 in numerical form to show typical neural network predictions for real-time constant flight condition simulation. The test PVV's for four flight conditions and the neural-network-based PVV's, using all three databases, are shown in Table 1. The present neural-network-based model is good for high-speed level flight, descent, climb, and a constant turn flight condition, Table 1.

The present neural-network-based approach involving the peak vibration was utilized in a quasi-static manner to simulate an extreme, time-varying maneuver. This maneuver has been considered earlier, the pull-up at 120 knots, counter 11022. The pull-up maneuver's experimental time histories for the pilot floor vertical acceleration, the pitch-rate, the collective, the lateral and longitudinal cyclics, and the PVV (test PVV) were shown in Figs. 1-4. A quasi-static approach will not capture all dynamic effects, and may miss the prediction of relevant maximums and their associated phases. Also, a time-series analysis using neural networks will capture the maximums and phases more accurately, compared to a quasi-static approach.

In the present quasi-static approach, the time history variations shown in Figs. 2 and 3 were represented by their average values over an 8-revolution segment length. Approximately 20 averaged values were thus used. These averaged parameter values were used to prepare the neural network inputs for databases 1-3. The previously trained neural networks, Figs. 10-12, were subsequently executed using the above discrete-values-based input time histories. Thus, three quasi-static real-time simulations were obtained for the PVV.

Figures 13a and 13b show the present quasi-static, neural-network-based predictions for the extreme time-varying maneuver, the pull-up, using both the maneuver load factor approach and the control stick positions approach, respectively. The time segments for the test PVV, Fig. 4, and those used in preparing the neural network inputs in Figs. 13a and 13b, were

exactly aligned with each other in time, i.e., had a zero offset. Figure 13a shows that neural-network-based and the test peak PVV's were within 0.02 g's of each other. Figure 13a also shows that the neural-network-based and the test peak PVV phases differed by approximately 1 second. The control stick positions approach, Fig. 13b, resulted in an overshoot of the PVV amplitude. The overshoot ranged from approximately 0.04 g's (database 2) to 0.10 g's (database 3). The peak PVV phase predictions differed by approximately 3 seconds for both cases, databases 2 and 3.

Figures 14a and 14b show exactly the same neural network results as in Figs. 13a and 13b, except that the Fig. 14 neural network results were offset by one half-segment. This was done to maintain physical consistency, i.e., in the time domain the neural network inputs must precede the resulting vibration that is being modeled, Figs. 14a and 14b. An appropriate value of the above offset can be determined by detailed parametric studies and was not done here. Figure 14a shows that neural-network-based and the test peak PVV's were within 0.02 g's of each other. Figure 14a also shows that the neural-network-based and the test peak PVV phases were approximately coincident.

For the pull-up maneuver under consideration, the maneuver load factor approach, Fig. 14a, gave better real-time simulation, i.e., resulted in greater overall fidelity with reasonably accurate peak prediction and only slight phasing differences, as compared to the control stick positions approach, Fig. 14b. The control stick positions approach again resulted in an overshoot of the peak PVV amplitude, Fig. 14b. The overshoot ranged from approximately 0.04 g's (database 2) to 0.10 g's (database 3). The peak PVV phase predictions differed by approximately 2 seconds for both cases, databases 2 and 3. The present use of a one half-segment offset was strictly empirical, and worked for the presently considered maneuver. A thorough and systematic variation of the offset involving the optimization of an appropriate cost function is required to obtain the best value of this important offset.

There are noticeable phase differences between the test PVV maximum and the neural-network-based PVV maximums for the control stick cases, Figs. 13b and 14b. This implies that in future studies, the time lag between the pilot control stick position inputs (collective, lateral and longitudinal cyclics) and the resulting PVV must also be accounted for when preparing the neural network inputs.

Conclusions

The present neural-network-based results showed that it was feasible to obtain reasonably accurate, real-time models of rotorcraft vibration under various flight conditions. The flight conditions considered were as follows: level flights, rolls, pushovers, pull-ups, autorotations, and landing flares.

For purposes of modeling UH-60A vibration, two analytical approaches were considered. This resulted in three neural network training databases. The first database involved a maneuver load factor that was derived using the helicopter roll-angle and its pitch-rate. The second and third databases involved the three pilot control stick positions. In the first and second databases, the helicopter gross weight was included as one of the neural network inputs. The third database was the same as the second database, except that the gross weight was not included. The resulting, trained back-propagation neural networks were small, implying rapid execution.

The present neural-network-based approach involving the peak pilot vibration was utilized in a quasi-static manner to simulate an extreme, time-varying pull-up maneuver. For the above pull-up maneuver, the maneuver load factor approach was better for real-time simulation, i.e., produced greater fidelity, as compared to the control stick positions approach. Thus, neural networks show promise for use in high-fidelity, real-time modeling of rotorcraft vibration for piloted simulations.

Acknowledgements

References

1. Aiken, E.W., Lebacqz, J.V., Chen, R.T.N, and Key, D.L., "Rotorcraft Handling-Qualities Design Criteria Development," NASA Conference Publication 2495, Volume II, NASA/Army Rotorcraft Technology Conference, March 1987.

2. Chen, R.T.N, Lebacqz, J.V., Aiken, E.W., and Tischler, M.B., "Helicopter Mathematical Models and Control Law Development for Handling Qualities Research," NASA Conference Publication 2495, Volume II, NASA/Army Rotorcraft Technology Conference, March 1987.

3. Sweeney, C., Sheppard, S, and Chetelat, M., "Development and Operation of a Real-Time Simulation at the NASA Ames Vertical Motion Simulator," AIAA Flight Simulation Technologies Conference, AIAA-93-3575, Monterey, California, August 1993.

4. Plonsky, J.G., Development of Equations to Improve Deficiencies in the GenHel UH-60A Math Model, Sikorsky Aircraft Division, United Technologies Corporation, NAS2-11058, 1989.

5. McCool, K.M., Flitter, L.A., aand Haas, D.J., "Development and Flight Test Evaluation of a Rotor System Load Monitoring Technology," American Helicopter Society 54th Annual Forum, Virginia Beach, Virginia, May 1998.

6. Haas, D.J., Milano, J., Flitter, L., "Prediction of Helicopter Component Loads Using Neural Networks," *Journal of the American Helicopter Society*, January 1995, pp.72-82.

7. McCool, K.M. and Haas, D.J., "Prediction of Helicopter Airspeed and Sideslip Angle in the Low Speed Environment," McCool K.M. and Haas, D.J., American Helicopter Society 53rd Annual Forum, Virginia Beach, Virginia, April-May 1997.

8. Kottapalli, S. "Neural Network Research on Validating Experimental Tilt-Rotor Performance," to be published in the July 2000 issue of the *Journal of the American Helicopter Society*. AIAA 16th Applied Aerodynamics Conference, AIAA-98-2418, Albuquerque, New Mexico, June 1998.

9. Kottapalli, S, "Application of Neural Networks to Aeromechanics Problems," 24th European Rotorcraft Forum, Marseilles, France, September 1998.

10. Kottapalli, S., "Exploratory Study on Neural Control of Rotor Noise and Hub Loads," American Helicopter Society Technical Specialists' Meeting for Rotorcraft Acoustics and Aerodynamics, Williamsburg, Virginia, October 1997.

11. Kottapalli, S., "Identification and Control of Rotorcraft Hub Loads Using Neural Networks," American Helicopter Society 53rd Annual Forum, Virginia Beach, Virginia, April-May 1997.

12. Kottapalli, S., Abrego, A., and Jacklin, S., "Application of Neural Networks to Model and Predict Rotorcraft Hub Loads," American Helicopter Society Second International Aeromechanics Specialists Conference, Bridgeport, Connecticut, October 1995.

13. Kottapalli, S. and Kitaplioglu, C., "Neural Network Representation of Experimental Tilt-Rotor Noise," 6th AIAA/CEAS Aeroacoustics Conference, AIAA-2000-1924, Maui, Hawaii, June 2000.

14. Kufeld, R.M., Balough, D.L., Cross, J.L., Studebaker, K.F., Jennison, C.D., and Bousman, W.G., "Flight Testing of the UH-60A Airloads Aircraft," American Helicopter Society 50th Annual Forum, Washington, D.C., May 1994.

15. Bondi, M.J. and Bjorkman, W.S., "TRENDS, A Flight Test Relational Database," User's Guide and Reference Manual, NASA TM 108806, June 1994.

16. Chen, R.T.N. and Jeske, J.A., "Kinematic Properties of the Helicopter in Coordinated Turns," NASA Technical Paper 1773, April 1981.

17. NeuralWorks Manuals: a) Reference Guide b) Neural Computing c) Using NeuralWorks, NeuralWare, Inc., Pittsburgh, Pennsylvania, 1995.

Table 1. Neural-Network-Based Predictions of Pilot Floor Vertical Vibration, PVV, g's

Flight Condition	Test	Maneuver Load Factor Database 1	Control Stick Database 2	Control Stick, No Weight Database 3
Level flight, 135 knots	0.10	0.09	0.10	0.11
Descent, 160 knots	0.25	0.24	0.25	0.26
Climb, 62 knots	0.12	0.12	0.12	0.12
Turn, 45 deg, 145 knots	0.13	0.13	0.13	0.14
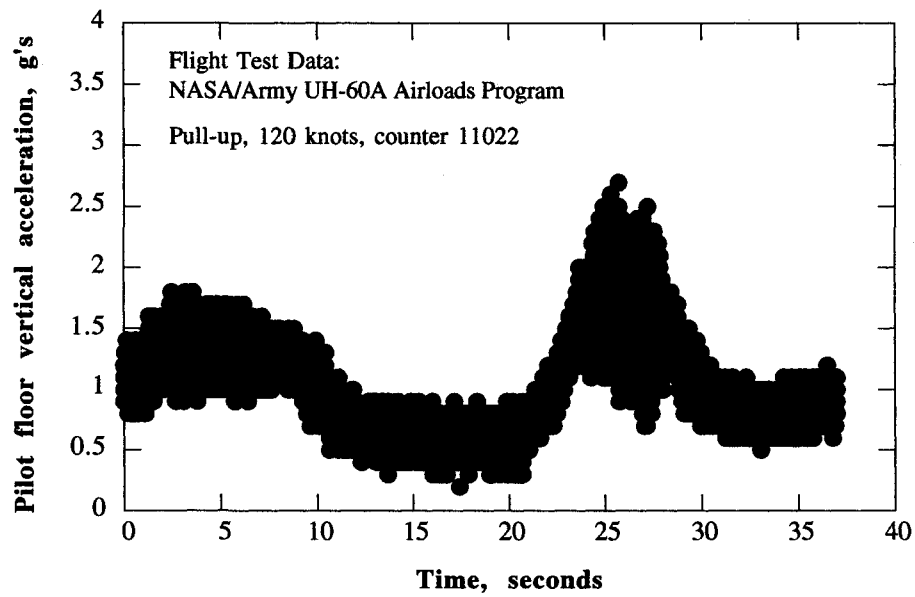
Fig. 1. Time history of pilot floor vertical acceleration, pull-up.
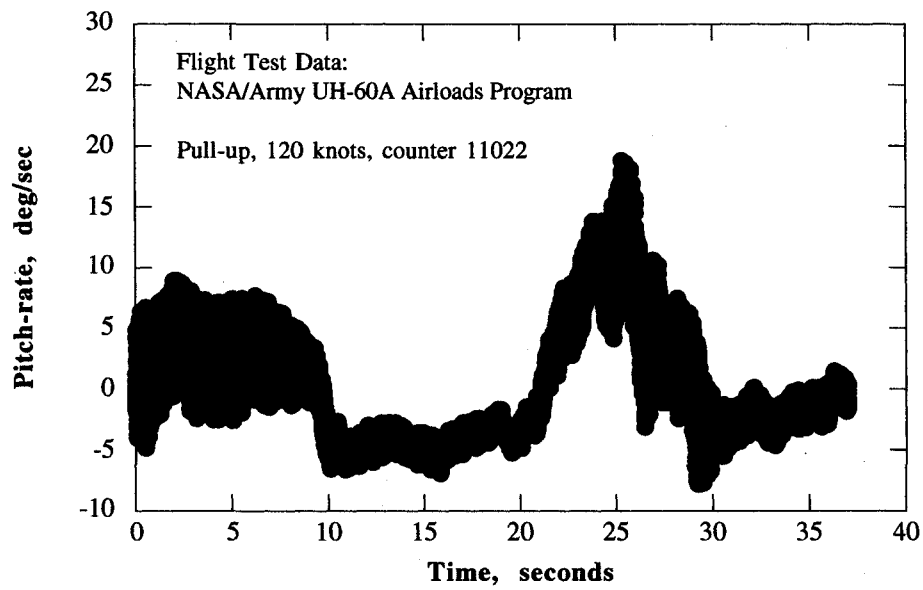
Fig. 2. Time-history of aircraft pitch-rate, pull-up.

9

American Institute of Aeronautics and Astronautics
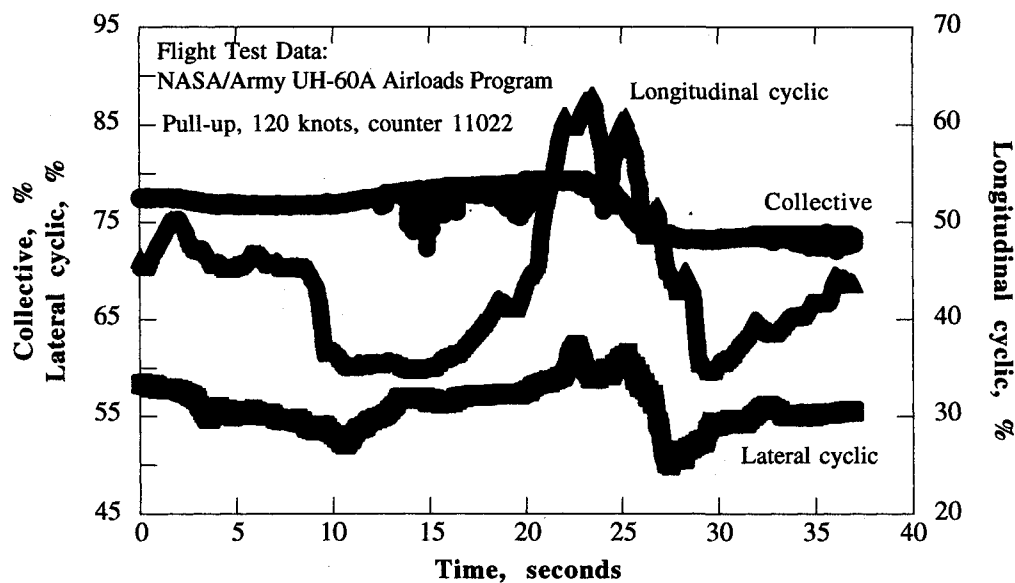
Fig. 3. Time histories of pilot control stick positions, pull-up.
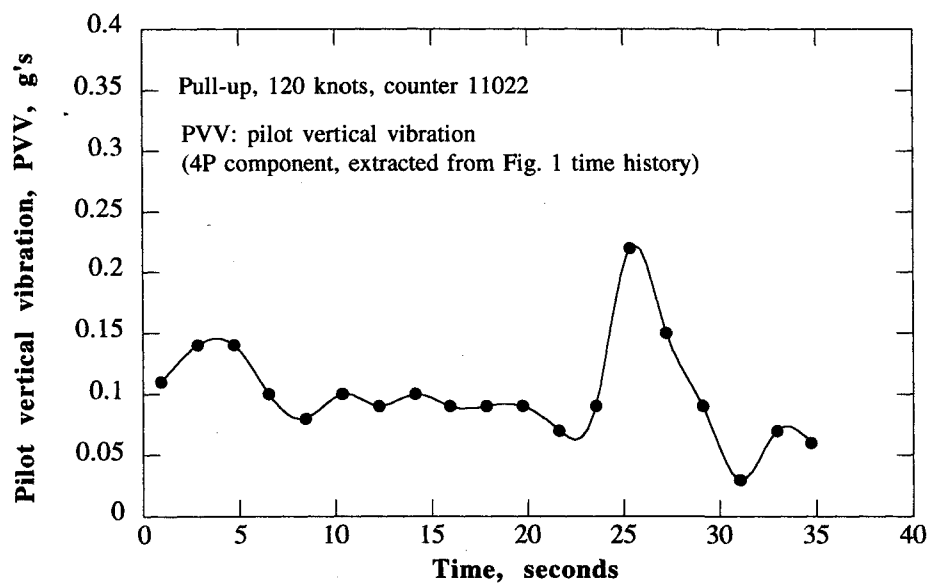
Fig. 4. Pilot vertical vibration, pull-up.
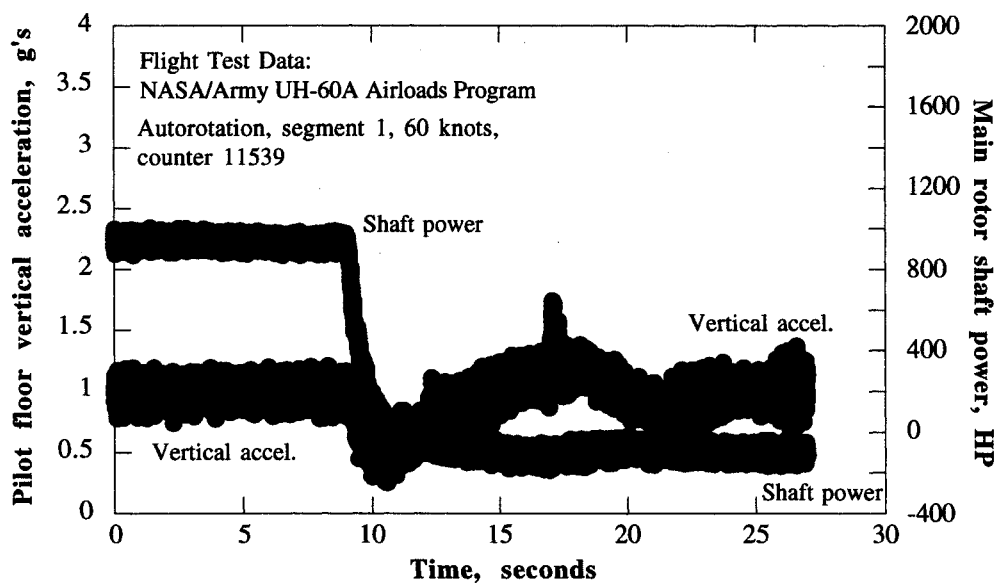
Fig. 5. Time histories of pilot floor vertical acceleration and rotor shaft power, autorotation, segment 1.
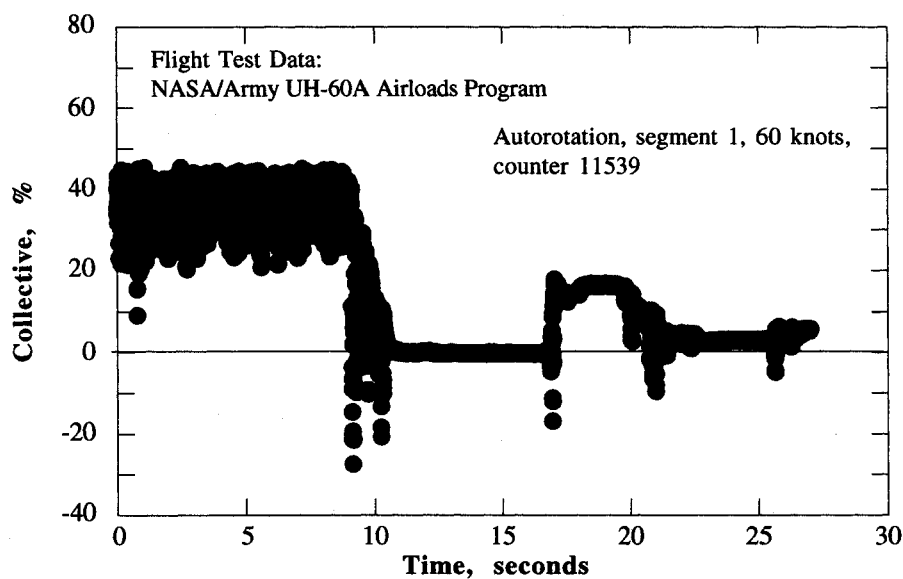
Fig. 6. Time history of collective stick position, autorotation, segment 1.
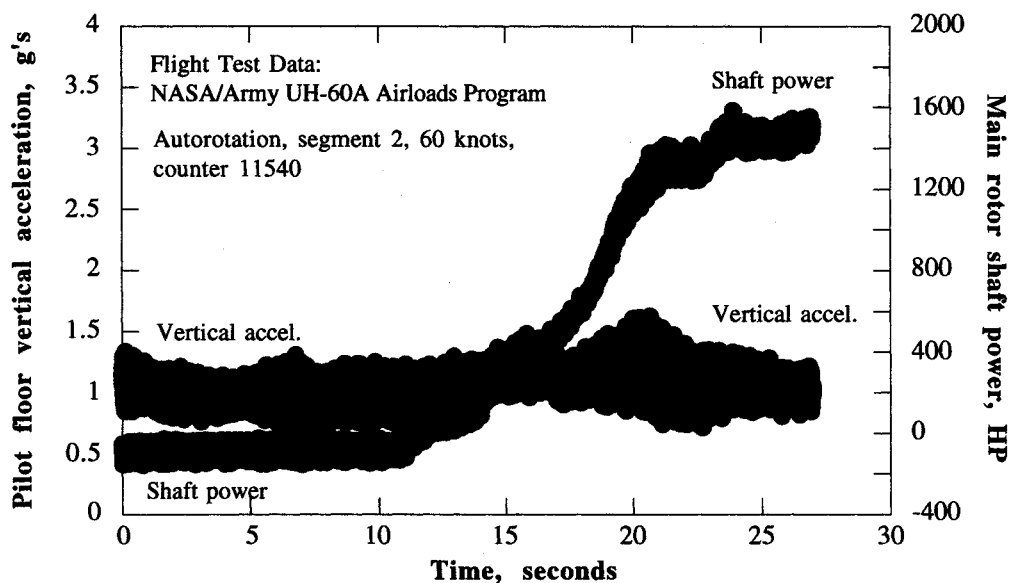
Fig. 7. Time histories of pilot floor vertical acceleration and rotor shaft power, autorotation, segment 2.
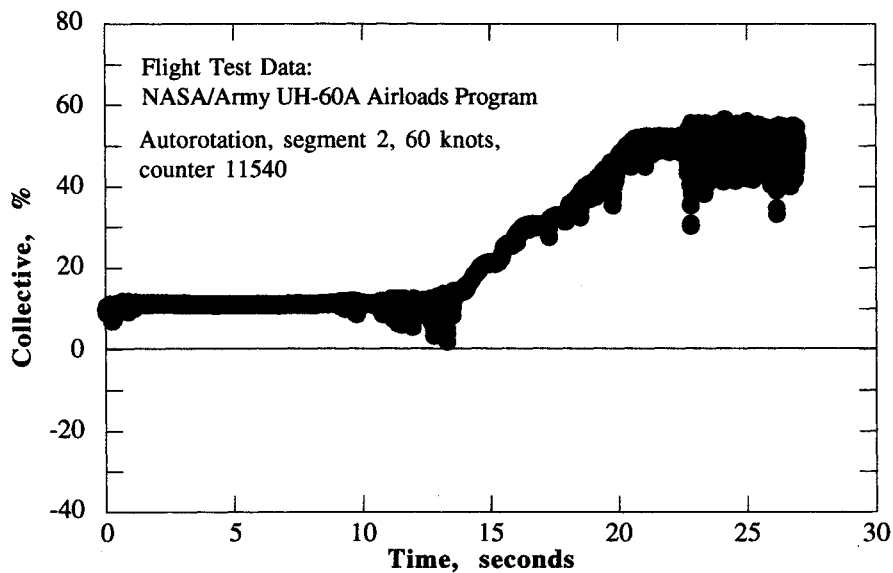
Fig. 8. Time history of collective stick position, autorotation, segment 2.
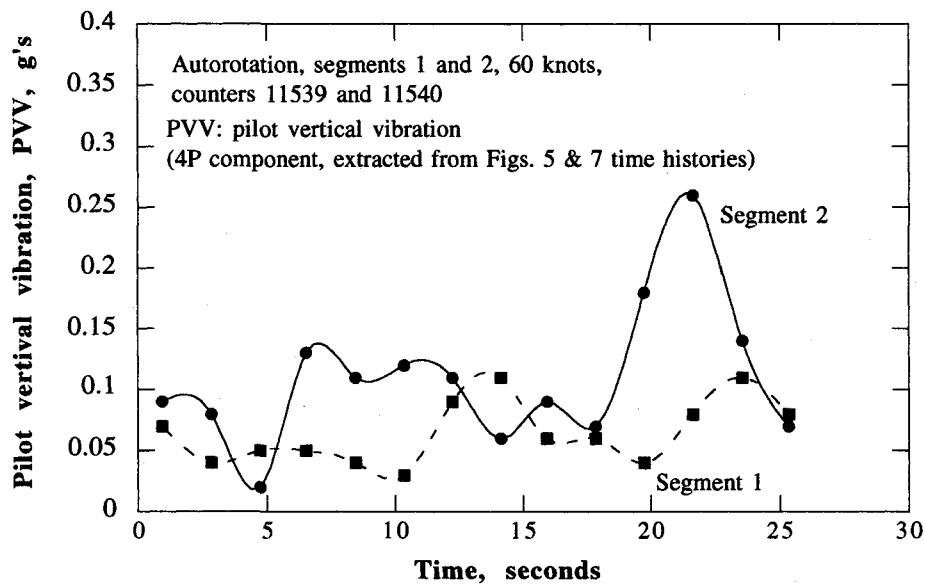
Fig. 9. Pilot vertical vibration, autorotation, segments 1 and 2.
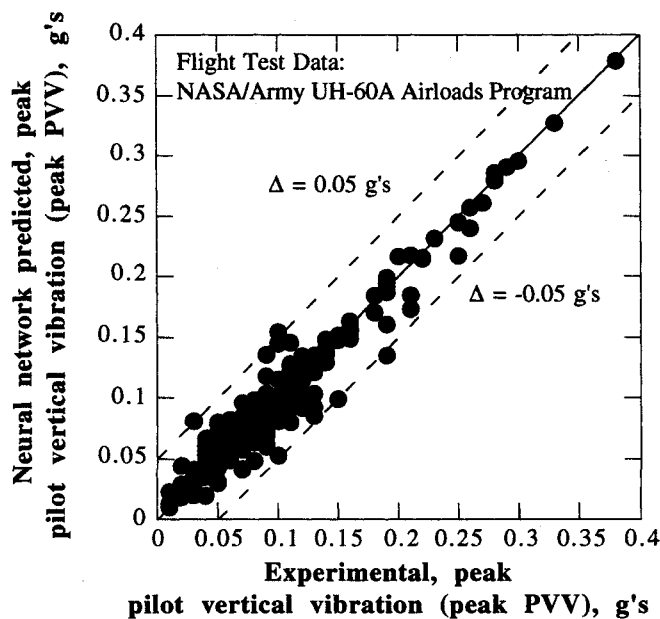
Fig. 10. Correlation, using "maneuver load factor," database 1.
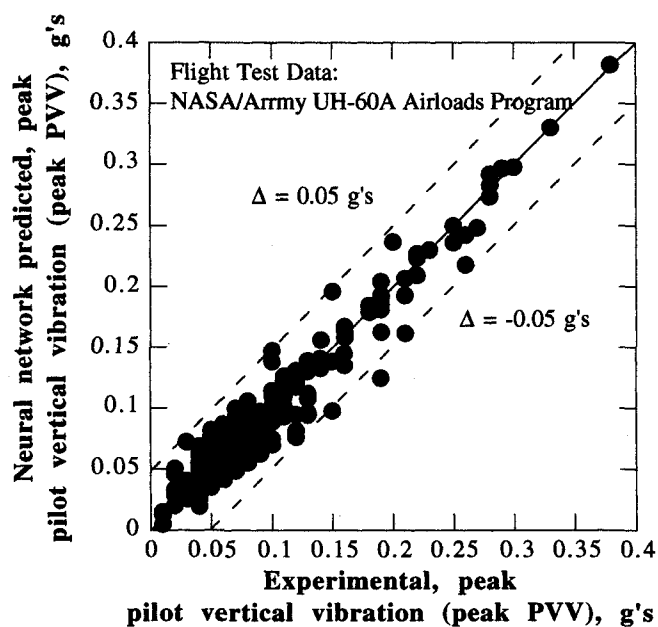
Fig. 11. Correlation, using pilot control stick positions, database 2.
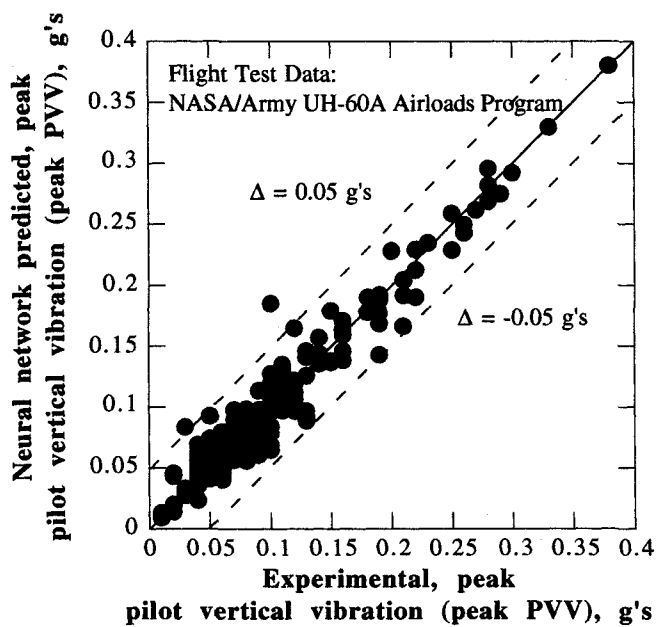
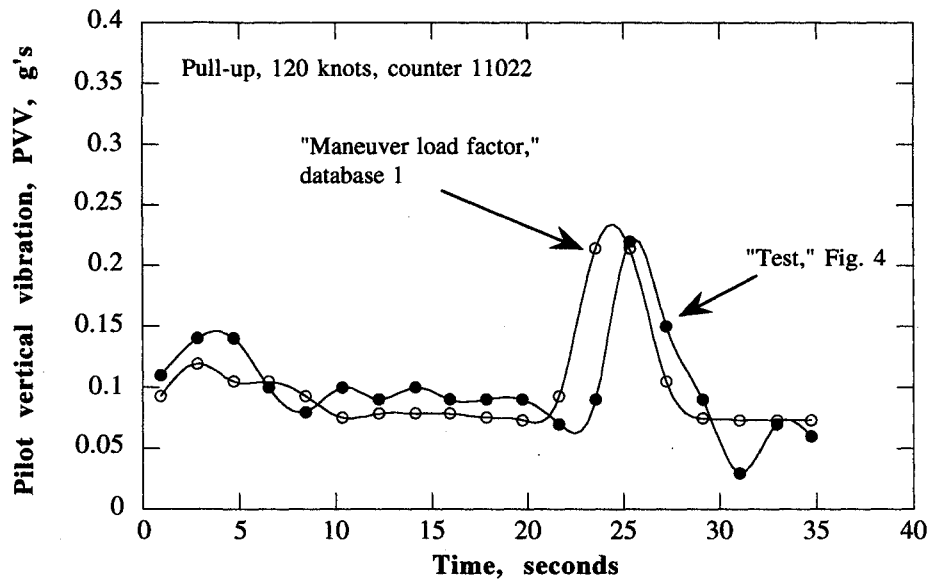Fig. 12. Correlation, using pilot control stick positions, weight not included, database 3.

Fig. 13a. Quasi-static real-time simulation using maneuver load factor, "zero offset," database 1.
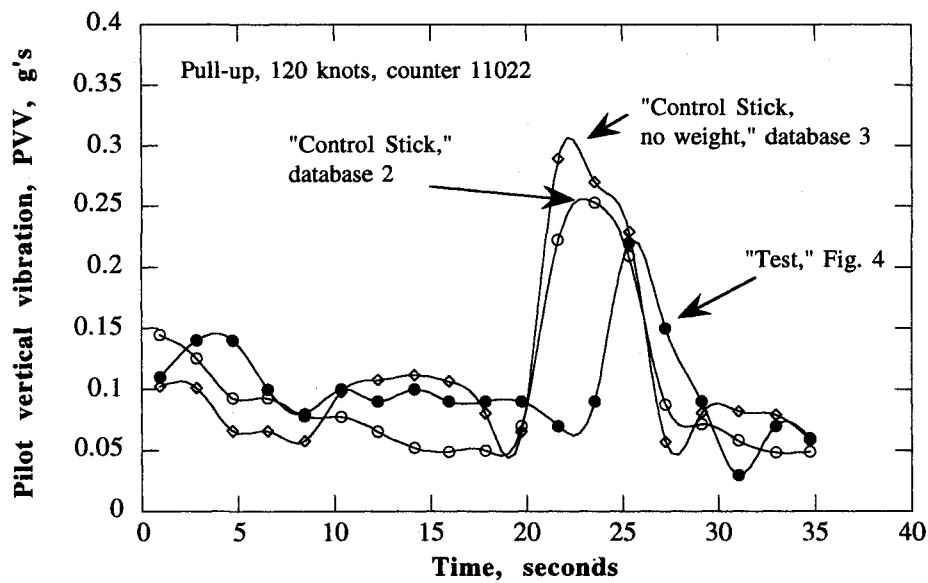

Fig. 13b. Quasi-static real-time simulation using control stick positions, "zero offset," databases 2-3.
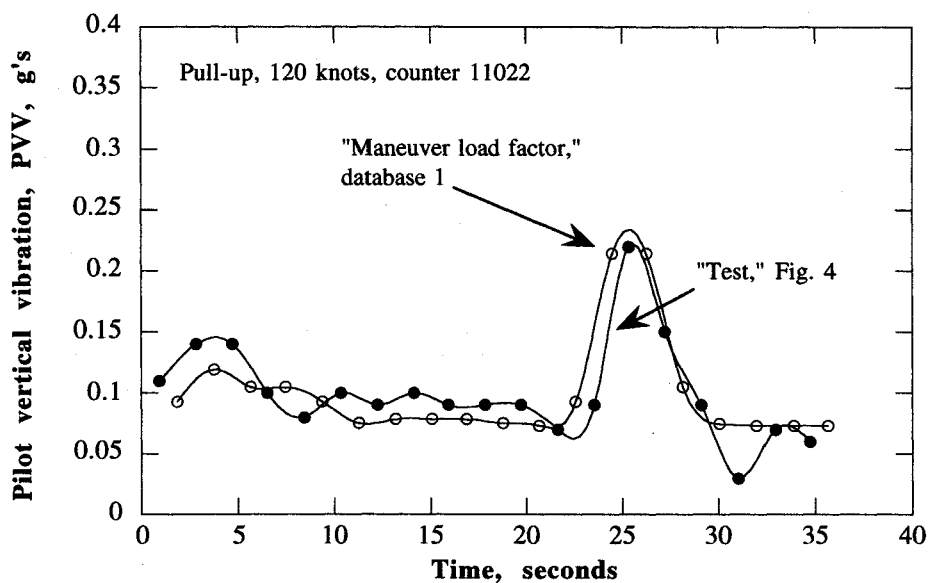
Fig. 14a. Quasi-static real-time simulation using maneuver load factor, "one half-segment offset," database 1.
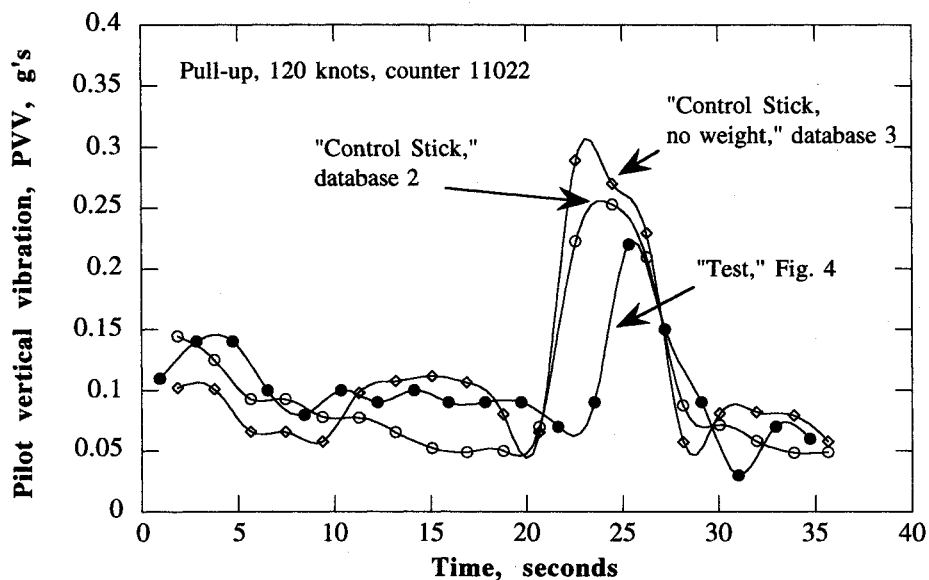

Fig. 14b. Quasi-static real-time simulation using control stick positions, "one half-segment offset," databases 2-3.